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# **WE SEE ICT SPILLOVERS EVERYWHERE BUT IN THE ECONOMETRIC EVIDENCE: A REASSESSMENT**

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# **We see ICT spillovers everywhere but in the econometric evidence: a reassessment**

## **Abstract**

Using company-level data for the US we study the productivity effects of knowledge spillovers, induced by the diffusion of ICT in the markets where companies operate. We adopt multiple spillover proxies and account for firms' absorptive capacity and lagged effects. Our results show that intra-industry ICT spillovers have a contemporaneous negative effect while the impact of inter-industry spillovers is positive. The overall productivity effect of ICT is negative, except for those companies with a strong absorptive capacity. However, after a 5-year lag the overall spillover effect turns positive while the role of absorptive capacity diminishes as a consequence of decreasing learning costs and more accessible technology.

JEL codes: D24, D62, O33

Keywords: Productivity, ICT Spillovers, Absorptive Capacity, R&D

## 1. Introduction

The diffusion of **Information and Communication Technologies (ICT)** has **revolutionised production processes, moving some of the sources of firms' competitiveness from inside to outside companies' boundaries. At the same time it has initiated a phase of** experimentation and collaboration, both within and outside the firm, accompanied by the creation of new knowledge that needs to be correctly assimilated and managed. It is widely acknowledged that both internal and external sources of knowledge (spillovers) are important to improve performance and need to be carefully assessed (Matusik and Heeley 2005, Jansen et al. 2005, Fabrizio 2009). So far there is substantial evidence on the positive impact of Information and Communication Technology (ICT) on productivity via the internal channel, especially when the new technology is coupled with investments in other intangible assets such as R&D, or organizational and human capital (Brynjolfsson and Hitt 2000, 2003, Kretschmer 2012). However, there is less clear support on the presence of ICT spillovers, i.e. on the contribution of ICT to the creation of external knowledge. **For example, there is no evidence of ICT spillovers in Stiroh (2002) or Acharya (2016) despite** the fact that these studies consider data for the US from the 1990s, a period of rapid ICT accumulation and a resurgence of productivity growth.

This paper investigates the presence of spillover effects associated with ICT in the US economy, re-examining this critical period and providing a new contribution to a controversy that has characterized the ICT and productivity literature over the past fifteen years. The focus on the 1990s allows us to look at the uptake of the digital economy, when firm heterogeneity is large and first-movers enjoy benefits which may cumulate over time. The 1990s also mark a period of acceleration of US productivity growth compared to regions such as Europe and we assess the extent to which the

presence of ICT spillovers has contributed to this trend (Jorgenson et al. 2008, Inklaar et al. 2008).

**Our main contribution is in the identification of four key elements that, taken together, play a major role in the estimation of the spillover effect.** First, we allow for different types of ICT spillover pools, namely those that originate among the firm's competitors and those which originate outside the industry. In doing so, we account for different types of external knowledge, which can have a different impact on companies' performance (Vega-Jurado et al. 2008). Second, we recognise that the ability of a firm to benefit from spillovers is determined by its capacity to assimilate the technological knowledge created outside the firm and to apply it within its production process. This absorptive capacity, or knowledge integration (Tell 2011), is a function of the firm's prior innovation effort, which is often proxied by the firm's investments in research and development and in workers' skills (Cohen and Levinthal 1989, 1990). A third element that we incorporate in our analysis is the assessment of the time at which ICT spillovers materialize. We recognise that there may be a lag between the assimilation of external knowledge and its effect on firm productivity performance (Brynjolfsson and Hitt 2003), i.e. the learning process is non-linear. Finally, we argue that industry data, commonly used in this literature, might be too aggregate to reveal the presence of spillovers.

**The main difference between our analysis and previous contribution on ICT spillovers is that, by including these four elements (spillover proxies, absorptive capacity, delayed effects and aggregation effects) within the same modelling framework, we provide a clearer understanding of how the effect of ICT spillovers propagates throughout the economy, the timing of the effect and the resources needed to internalize its benefits.** Our work captures the different

channels of transmission of ICT spillovers by constructing two proxies for ICT-related external knowledge. We first evaluate whether companies' productivity performance is affected by the total stock of ICT capital within each industry. This is a valid measure to assess the presence of intra-industry spillover effects whereby, for example, the activity of a microelectronics company benefits from the adoption of ICT within the whole electrical and optical equipment industry. However, such *intra-industry* effect might only provide a partial assessment of the role of aggregate ICT as it does not account for the possibility of spillovers across industries. In fact, companies can benefit from the adoption of ICT by upstream and downstream industries, via, for example, improved service provisions (financial and shipping services). This *inter-industry* effect is assessed by means of a weighted ICT industry variable, where the weights capture the degree of companies' proximity, measured either in terms of intensity of transactions (using input-output coefficients of intermediate transactions) or technological proximity (using patent citation flows). The impact of weighted ICT spillover measures has been studied at the industry level in the US (Mun and Nadiri 2002) but little is known about the transmission of different ICT spillover pools at the firm level.

Throughout the analysis we assess the role of absorptive capacity using the cumulative value of R&D expenses and the interaction of this variable with the ICT spillover proxies. Our work also accounts for contemporaneous and lagged impacts of ICT spillovers on productivity by including various lags of both ICT and the interaction terms, hence providing a test of the 'delayed hypothesis', which underlies the GPT framework (Brynjolfsson and Saunders 2009). This approach allows the investigation of how the productivity effects of absorptive capacity may change through time, an aspect that has often been overlooked in

existing work (Matusik and Heely 2005, Tell 2011). Our study provides **two novel pieces of evidence to the literature on the drivers of productivity and on knowledge spillovers. First, we document that the external knowledge associated with the industry-level diffusion of ICT yields important productivity gains at the company level. Although the contemporaneous intra-industry spillover effect is negative**, due to the costs of assimilating the new knowledge, the impact turns positive some years after investment. Our estimates show that it takes approximately 5 years for intra-industry spillovers to positively affect productivity performance. By contrast, the effect of inter-industry spillovers is always positive and significant. **Second, our results show that a company's absorptive capacity is crucial in the early stage of technological diffusion. In fact, a company's R&D is complementary to ICT spillovers and only in the most innovative firms does the positive inter-industry spillover offset the negative intra-industry effect. However, such complementarity disappears over time, with the more pervasive adoption and diffusion of the technology.**

Our findings are important because assessing the presence and the timing of such spillovers provides economists, managers and policy makers with the right measures to foster competitiveness and long-run growth (Bresnahan 1986). The lack of evidence on the existence of ICT spillovers has lead researchers to doubt the importance of General Purpose Technology (GPT) effects related to ICT (Draca et al. 2007) and might have prevented or slowed down the adoption of policies aimed to facilitate the absorption and diffusion of new technologies. In regions like Europe, which are still experiencing stagnant productivity growth, understanding the forces that have contributed to the productivity revival in the US is necessary to improve

productivity performance and resume the catching up process of the early 1990s (Daveri 2004, Miller and Atkinson 2014).

The following section discusses the main sources of ICT spillovers and presents an overview of the existing empirical evidence (Section 2). Section 3 presents the model used in the empirical analysis and provides examples of the spillover effect captured by our two proxies. Section 4 presents the data and summary statistics. Our econometric findings are shown and discussed in Section 5. Section 6 concludes the paper.

## **II. RELATED LITERATURE**

Despite some skeptical views on the importance of the new technological revolution it is undeniable that computers and their countless applications have changed the organization of the firm, the structure of the industry and many aspects of economic and social interactions. For these reasons ICT has been recognized as a General Purpose Technology (GPT).

The relationship between ICT and productivity has spurred particular interest and a review of a wide range of studies, based on different analytical techniques, suggests that a 10% increase in ICT increases labour productivity growth by approximately 0.5% (Kretschmer 2012).<sup>1</sup> Several studies have also tried to assess whether ICT is a ‘special’ type of asset, and as such able to generate important productivity spillovers, i.e. increases in productivity in addition to the contribution of capital deepening (O'Mahony and Vecchi 2005, Venturini 2015). As a General Purpose Technology (GPT) ICT reconciles different explanations of knowledge spillovers. It is undisputable that the adoption and diffusion of ICT has generated a vast increase in knowledge transfers across individuals and such transfer of ideas



contributes to knowledge exploitation and can be a main contributor to organizational changes, innovations and growth.

Within firms, the use of computers and software has increased over time, leading to changes in production techniques and organizational structure, a process that can be considered an example of learning-by-doing type of externalities (Arrow 1962). ICT has also greatly facilitated the 'learning from others' process, by opening up opportunities for gathering and sharing information, both within and outside the firm (Aghion 2002). For example, the use of electronic data interchange, internet-based procurement systems and other inter-organizational information systems has led to a reduction in administrative and search costs, and better supply chain management (Rowlatt 2001, Criscuolo and Waldron 2003).

Another type of externality generally associated with ICT is network externality, which arises when the value of a product or service increases as it is adopted by more users (Brynjolfsson and Kremerer 1996)<sup>2</sup>. An early theoretical discussion of network externalities can be found in Katz and Shapiro (1985), in relation to consumption externalities, whereby consumers derive more utility from participating in a network depending on the number of people using the same network, the variety of products that a network provides and the quality of the post-purchase service network. Several empirical contributions support the presence of network externalities linked to ICT, for example in relation to the computer spreadsheet market (Gandal 1994), the diffusion of home computers (Goolsbee and Klenow 2002) and electronic payment (Gowrisankaran and Stavins 2002).

Although the possibilities for ICT spillovers are numerous, the impact of such spillovers on productivity is more dubious and so far the empirical analysis has provided weak support (Cardona et al. 2013). For example, Stiroh (2002), using a

TFP growth regression, finds no evidence of positive spillovers from ICT capital, nor evidence of positive spillovers from individual components (computer capital and telecommunication capital) in the US economy. **Results for European countries in Inklaar et al. (2008) also reveal the absence of ICT spillovers.** Haskel and Wallis (2010) reach similar conclusions in the UK and Acharya (2016) fails to find positive ICT spillovers in an industry-level analysis for 16 OECD countries. A common feature of these studies is that they are based on industry-level data, hence their results could be affected by an aggregation bias, as discussed in Brynjolfsson and Hitt (2000) and Haskel and Wallis (2010)<sup>3</sup>. However, even at the firm level, the econometric evidence is inconclusive. For example, Van Leeuwen and van der Wiel (2003) show that ICT spillovers positively affect labour productivity in Dutch companies operating in market services, while Moshiri and Simpson (2011) reject the presence of ICT spillovers among Canadian firms. **More recently, Moshiri (2016) finds that the manufacturing and service sectors in Canada benefit from ICT spillovers from the US, while there is no effect in the primary sector. Firm level evidence for the US is quite scarce and does not always assess the importance spillovers. For example, Brynjolfsson and Hitt (2003) find that firms' investments in computer hardware yield excess returns when considering long lags. This suggests that within firms spillovers are present in the US economy but it does not provide any insights of how companies can benefit from external sources of knowledge. More recently, Tambe and Hitt (2014) provide some evidence of an ICT spillover effect in US companies but only consider a possible channel of knowledge diffusion (IT workers' flows on local labour markets).**

A central issue for the identification of the spillover effect is the proxy used to capture the external knowledge. Most of the evidence to date only considers that

spillovers might operate within industries (Stiroh 2002, Basu and Fernald 2007). However, this implicitly assumes that there is a single source of knowledge that can impact on companies' performance. This assumption is opposed to the view that knowledge can be characterized by different levels of complexity (Lane et al. 2006) and can originate from different sources, both within and outside the industry. Indeed companies can benefit from the adoption of ICT by their suppliers or clients as well as competitors (Cohen and Levinthal 1990). The nature of this knowledge is likely to differ depending on the source. Competitors are more likely to be the font of more technical industry-specific knowledge, related for example to the re-structuring of the production process; conversely, actors along the supply chain can be the source of the increased efficiency of transactions. Measuring the effect of such a complex network of interactions requires the construction of suitable spillover pools. The literature on R&D spillovers has frequently used weighted measures of aggregate R&D that capture industries/firms' technological distance (Jaffe 1986). However, this approach has been less popular in constructing ICT spillover pools (Mun and Nadiri 2002, Wolff 2011, Moshiri and Simpson 2011).

Identifying different types of external knowledge is important for the evaluation of the role of companies' absorptive capacity, i.e. their ability to identify the relevant knowledge generated outside the firm, assimilate it and turn it into competitive advantage (Cohen and Levinthal 1989). This is an aspect of the relationship between ICT spillovers and productivity that has been discussed at length in several contributions but where the econometric analysis is still lagging. Spillovers from ICT, like other types of spillovers, are likely to require firms' prior effort in innovative activities; however, the empirical analysis has mainly analyzed the importance of absorptive capacity in relation to R&D spillovers (Cohen and Levinthal

1989, 1990, Griffith et al. 2004). Conversely, it is possible that there is a complementary relationship between firm's R&D and ICT spillovers, which goes beyond the fact that ICT has originated from research effort (Guellec and van Pottelsberghe 2004).<sup>4</sup> Recent evidence at the industry level further extends this concept by showing the complementarity of ICT not only with R&D but with a whole set of other intangible assets (Corrado et al. 2014). Despite the apparent relevance of absorptive capacity, only a handful of firm-level studies address this issue in relation to ICT spillovers and the results so far do not support the complementary relationship between R&D and ICT (see for instance Hall et al. 2013 and Polder et al. 2010).

Another relevant issue for the identification of ICT spillovers is the specification of an empirical model that can capture the lagged impact of spillovers on productivity. A large empirical literature has shown that ICT adoption imposes long periods of experimentation, during which companies undertake investments in organization and human capital (Brynjolfsson and Hitt 2003). This implies a substantial delay in the ICT impact on productivity performance, which also justifies the presence of lagged ICT spillovers. Some evidence on this effect can be found in Basu et al. (2004), Basu and Fernald (2007) and Brynjolfsson and Hitt (2003). However, the majority of firm level studies focus on contemporaneous spillover effects,<sup>5</sup> which may well be negative or non-statistically significant because of the presence of adjustment costs.

Related to this, existing studies have not provided any insights on how absorptive capacity may affect performance over time. Following the argument of the cumulative process of knowledge and the importance of long-term complementarities between skills and new technologies, we expect the effect of absorptive capacity to increase over time. **However two factors can affect this trend. The first one is**

external to the firm and relates to the possibility that further technological developments lead to a more codified technology that is easier to access and implement (Chun 2003, Mason et al. 2008). The second factor is a direct consequence of the firm's learning process, which implies high costs (in terms of absorptive capacity) in the initial adoption phase and lower costs as the learning improves<sup>6</sup>. In both situations, further increases in absorptive capacity might no longer be necessary to assimilate the ICT spillover (Cohen and Levinthal 1990); hence a test of the 'delay hypothesis' is necessary to fully assess the importance of ICT spillovers and absorptive capacity.

### III. MODELLING THE IMPACT OF ICT SPILLOVERS ON PRODUCTIVITY

We model the output of a single firm as a function of its own inputs and an index of aggregate activity. Similarly to Jones (1968), we assume that spillovers are related to the scale of the industry ICT and are external to the decisions taken by any firm, so as to retain the perfectly competitive nature of the model. The starting point of our analysis is a Cobb-Douglas production function, where output ( $Y_{ijt}$ ) is expressed as a function of labour ( $L_{ijt}$ ), physical capital ( $K_{ijt}$ ), and R&D capital ( $R_{ijt}$ ):

$$Y_{ijt} = A(ICT_{jt})L_{ijt}^{\alpha}K_{ijt}^{\beta}R_{ijt}^{\gamma} \quad (1)$$

where  $i$  denotes firm,  $j$  industry and  $t$  time. The term  $A$  is the firm's total factor productivity and it is determined by an industry measure of ICT capital. The coefficients  $\alpha$ ,  $\beta$  and  $\gamma$  denote the elasticities of output with respect to labour, physical capital and R&D respectively. Constant returns to scale occur when  $\alpha + \beta + \gamma = 1$ , a hypothesis that we will test in our analysis. Expressing equation (1) in per-worker terms and denoting logarithms with lower case variables, we can re-write the production function as follows<sup>7</sup>:

$$\left(\frac{y}{l}\right)_{ijt} = \alpha_i + \chi(ICTL)_{jt} + \beta \left(\frac{k}{l}\right)_{ijt} + \gamma \left(\frac{r}{l}\right)_{ijt} + \varepsilon_{ijt} \quad (2)$$

As discussed in the previous section, ICT facilitates knowledge transfers across firms and this can lead to important productivity spillovers. For example, a firm  $i$  operating in industry  $j$  can easily access information about its competitors, their range of products, prices and additional services, via an Internet search engine and use such information for its own production and/or marketing strategy. Also, firms may easily imitate best practices from first-move adopters in the same industry, reaping important productivity benefits. This *within or intra-industry* spillover captures the idea that firms learn in areas closely related to their experience (Kogut and Zander 1993, Nelson and Winter 1982). In our analysis this is measured by the total stock of ICT at the industry level (defined as  $ICTL_{jt}$ ). However, spillovers can also originate from the knowledge created in companies/industries which are located in industries other than its own (Schmidt 2010). In fact, ICT facilitates knowledge acquisition about firms' suppliers (prices, type of products and services, innovative practices) as well as firms' clients (personalized offers based on client's previous purchases), which can feed into the firm's production function and lead to productivity gains. Hence, ICT may also be a source of *between or inter-industry* spillovers, which are likely to be stronger the larger the number of firms adopting the new technology. Hence the inter-industry variable is also capturing the effect of network spillovers.

To trace inter-industry flows of spillovers we use industry series on ICT, weighted by input-output intermediate transactions' coefficients, denoted by  $wICTL_{jt}$  and constructed as follows:<sup>8</sup>

$$wICTL_{jt} = \sum_{j=1}^{16} w_{jft} \times ICTL_{ft} = \sum_{j=1}^{16} \frac{M_{jft}}{Y_{ft}} \times ICTL_{ft} \quad (3)$$

with  $f \neq j$  and  $t=1991, \dots, 2001$ .  $ICTL_j$  is the ICT capital stock per worker in the industry  $j$  where company  $i$  is located.  $ICTL_f$  is the value of the surrounding industries ( $f \neq j$ ).  $w_{jft}$  is the inter-industry coefficient of intermediate transactions between industry  $j$  and industry  $f$ , defined as ratio between the flow of intermediate inputs sold by industry  $f$  to industry  $j$  and the gross output of the selling sector, respectively denoted by  $M_{jft}$  and  $Y_{ft}$ . This procedure eliminates the bias associated with the different scale between the ‘selling’ and the ‘purchasing’ industry, as discussed in Lichtenberg and van Pottelsberghe (1998) in relation to international technology spillovers. Introducing the effect of the two spillover channels, our empirical specification can be written as (benchmark model):

$$\left(\frac{y}{l}\right)_{ijt} = a_i + \beta \left(\frac{k}{l}\right)_{ijt} + \gamma \left(\frac{r}{l}\right)_{ijt} + \chi_1 ictl_{jt} + \chi_2 wictl_{jt} + \sum_{t=1}^{10} \delta d_t + \varepsilon_{ijt} \quad (4)$$

where the dependent variable is labour productivity,  $a_i$  is a company specific intercept (fixed effect) which, among others, **captures the time-invariant effect of other intangible factors (organizational inputs, management practices, etc.) that are not available from company accounts**. The coefficients  $\beta$  is the elasticity of labour productivity to capital per worker (capital deepening),  $\gamma$  identifies the R&D elasticity,  $\chi_1$  captures externalities directly associated with *intra-industry* spillovers and  $\chi_2$  captures the effect of *inter-industry* knowledge transfers. Both ICT variables are normalized by industry employment in order to neutralize possible scale effects on firm performance and identify the average value of ICT capital available to each worker in the sector ( $ICTL_{jt}$ ).  $d_t$  are **common time dummies, which allows the identification of any spillover effect net of other cyclical and/or exogenous components (Oulton 1996)**.

Due to data constraints, we are not able to distinguish between ICT and non-ICT capital at the company level, and therefore we cannot separately identify

industry-wide spillovers from the productivity effect of a firm's own ICT capital. Existing company level studies have attempted to assess the ICT capital elasticity using crude proxies for firm ICT. Given the shortcomings of these measures, which are well known in the related literature, their use does not fully address the possible mis-specification issue.<sup>9</sup> In addition, new vintages of capital have increasingly included computer equipment and have become more dependent on computer software. Therefore, part of the ICT impact will be captured by our fixed capital measure.

### **III.b Spillovers and absorptive capacity**

The introduction of R&D in our modelling framework allows us to assess the presence of complementarities between R&D and ICT, and to test directly whether the impact of ICT spillovers depends on companies' absorptive capacity. Measuring absorptive capacity is complex because of the intangible and multi-dimensional nature of the phenomenon (Zahra and George 2002, Matusik and Heeley 2005, Camisón and Forés 2008, Schmidt 2010)<sup>10</sup>. Here we refer to Cohen and Levinthal (1989, 1990) who consider R&D as a determinant of new knowledge and as a factor that enhances a firm's ability to exploit knowledge generated elsewhere, hence defining R&D as the main conduit of the spillover effect. Subsequent work has considered other determinants such as workers' skills, organizational structure and management practices (Vinding 2006, Schmidt 2010, Lane et al. 2006). These additional measures, although conceptually relevant, are likely to be highly correlated with R&D and this would make the empirical identification of separate effects particularly challenging (Goedhuys et al. 2013). For example, Vega-Jurado et al. (2008) point out that technological competences, generally measured by R&D, are not



independent of human resources competences, organizational competences and skills. Indeed, a large proportion of a firm's R&D expenditure is directed towards the wage of highly skilled employees, namely R&D scientists and engineers (Shankerman 1981, Guellec and van Pottelsberghe 2004).

To model the mechanisms for the assimilation of the spillover effect we follow Griffith et al. (2004) and we expand equation (4) to include the interaction between company's R&D capital and our measures of ICT spillovers:

$$\left(\frac{y}{l}\right)_{ijt} = a_i + \beta \left(\frac{k}{l}\right)_{ijt} + \gamma \left(\frac{r}{l}\right)_{ijt} + \chi_1 ictl_{jt} + \eta r_{ijt} * ictl_{jt} + \chi_2 wictl_{jt} + \rho r_{ijt} * wictl_{jt} + \sum_{t=1}^{10} \delta d_t + \varepsilon_{ijt} \quad (5)$$

where  $\eta$  and  $\rho$  are the portion of ICT spillovers acquired by the firm through its knowledge base (i.e. its absorptive capacity). The total impact of *intra-industry* ICT spillovers is therefore given by  $\chi_1 + \eta r_{ijt}$ , evaluated at different points of the R&D distribution. Equation (5) models the possibility that firms may benefit from ICT spillovers by means of their absorptive capacity ( $\eta > 0$ ,  $\chi_1 = 0$ ), directly without any R&D investments ( $\eta = 0$ ,  $\chi_1 > 0$ ), or more widely through both channels ( $\eta > 0$ ,  $\chi_1 > 0$ ). In the same way, we can calculate the total impact of *inter-industry spillovers*. As a result, the *overall* spillover effect from ICT will be given by the sum of the two types of spillovers.

#### IV. DATA SOURCES AND DESCRIPTIVE STATISTICS

Our analysis makes use of US company accounts from the Compustat database for the period 1991-2001. Our study therefore covers the entire cycle of the New Economy growth, from the earlier phases of ICT uptake to the collapse of the ICT bubble in the stock market. Focusing on this period allows us to analyze the presence of spillovers during the uptake of a new technology, as well as making our results comparable with the existing evidence. We extract information on net sales, employment, net physical

capital, defined as equipment and structures (PPE), and R&D expenditures. Full details on data sources and methods can be found in the working paper version of the manuscript.<sup>11</sup> Net physical capital at historic cost is converted into capital at replacement cost (Arellano and Bond 1991). R&D expenditure is converted into a stock measure using a perpetual inventory method, together with the assumption of a pre-sample growth rate of 5% and a depreciation rate of 15% (see Hall 1990 for details). The use of R&D capital stocks accounts for the accumulation of knowledge and makes current R&D efforts dependent on past endeavors. This should better capture the cumulative nature of absorptive capacity, frequently discussed in the literature (Cohen and Levinthal 1990, Zahra and George 2002, Matusik and Heeley 2005, Vega-Jurado et al. 2008).

The Compustat database classifies companies into industries according to the 1987 US Standard Industrial Classification (SIC). This classification is then converted into ISIC Rev. 3 base, which is the one followed by the industry-level variables. We merge company- and industry-level sources, obtaining a consistent data set for seventeen industries (twelve manufacturing plus five service industries).

Industry accounts data (ICT, employees, etc.) come from EU KLEMS 2011, while R&D expenditure is from OECD ANBERD 2009. Input-output intermediate transactions' coefficients are taken from the OECD I-O output table at benchmark years and are interpolated for intermediate observations. Both ICT and R&D variables are normalized on industry employment in order to neutralize possible scale effects on firm performance and identify the average value of ICT per capital available to each worker in the sector.

**TABLE 1**  
Descriptive Statistics (1991-2001)

|                                 |                            | Obs   | Mean  | SD    | Min    | Max   |
|---------------------------------|----------------------------|-------|-------|-------|--------|-------|
| <i>Company characteristics</i>  |                            |       |       |       |        |       |
| $Y/L_{ijt}$                     | Output                     | 9,293 | 0.261 | 0.565 | 0.0001 | 24.2  |
| $K/L_{ijt}$                     | Physical capital           | 9,417 | 0.263 | 3.982 | 0.0001 | 193.7 |
| $R/L_{ijt}$                     | R&D capital                | 9,330 | 0.088 | 0.156 | 0.0001 | 2.85  |
| <i>Industry characteristics</i> |                            |       |       |       |        |       |
| $ICTL_{jt}$                     | Intra-industry ICT capital | 9,480 | 0.048 | 0.051 | 0.0001 | 0.367 |
| $wICTL_{jt}$                    | Inter-industry ICT capital | 9,480 | 0.039 | 0.033 | 0.0049 | 0.182 |
| $RDL_{jt}$                      | Intra-industry R&D capital | 9,480 | 0.395 | 0.431 | 0.0006 | 1.125 |
| $wRDL_{jt}$                     | Inter-industry R&D capital | 9,480 | 0.106 | 0.133 | 0.0012 | 0.529 |

Notes: All variables are expressed in millions of 1995 USD per worker.

Table 1 presents descriptive statistics for the variables used in the regression analysis. We work with an unbalanced panel of 968 firms. Average net sales amounted to \$0.261 million per worker (at 1995 prices), physical capital stock to \$0.263 million, while firm R&D capital was \$0.088. At industry level, the stock of ICT per worker,  $ICTL$ , is considerably smaller than R&D (\$0.048 against \$0.395 million per worker). Whereas for ICT assets intra- and inter-industry capital values are comparable in size ( $ICTL$  vs  $wICTL$ ), the cumulative value of intra-industry R&D sizably exceeds the inter-industry variable ( $RDL$  vs  $wRDL$ ). This shows that R&D investment was largely concentrated across sectors while ICT was adopted more pervasively after the digital revolution.

Table 2 displays industry distributions of firm R&D stock and industry-level variables. Communication services and transport equipment have the highest levels of company knowledge capital, followed by chemicals and business services. Service industries denote the highest levels of intra-industry ICT per worker ( $ICTL_{jk}$ ), while inter-industry ICT ( $wICTL_{jk}$ ) is higher in manufacturing industries due to their more intensive inter-industry linkages.

**TABLE 2**

Average Company R&D and Spillover Proxies by Industry (1991-2001)  
millions USD at 1995 prices

|       |                              | $R/L_{ijk}$ | $ICTL_{jk}$ | $wICTL_{jk}$ | $RDL_{jk}$ | $wRDL_{jk}$ |
|-------|------------------------------|-------------|-------------|--------------|------------|-------------|
| 15t16 | Food& Beverage               | 0.025       | 0.020       | 0.045        | 0.048      | 0.080       |
| 17t19 | Textile, Clothing & Footwear | 0.013       | 0.006       | 0.070        | 0.014      | 0.442       |
| 20    | Wood                         | 0.013       | 0.006       | 0.016        | 0.002      | 0.061       |
| 21t22 | Pulp, Paper & Publishing     | 0.024       | 0.025       | 0.022        | 0.042      | 0.062       |
| 24    | Chemicals                    | 0.207       | 0.086       | 0.023        | 0.910      | 0.028       |
| 25    | Rubber&Plastics              | 0.201       | 0.010       | 0.031        | 0.088      | 0.243       |
| 26    | Non-metallic minerals        | 0.012       | 0.022       | 0.013        | 0.068      | 0.050       |
| 27t28 | Basic metals, etc.           | 0.009       | 0.016       | 0.013        | 0.050      | 0.050       |
| 29    | Machinery                    | 0.044       | 0.037       | 0.048        | 0.170      | 0.209       |
| 30t33 | Electrical equipment         | 0.086       | 0.052       | 0.042        | 0.877      | 0.02        |
| 34t35 | Transport equipment          | 0.019       | 0.032       | 0.092        | 0.924      | 0.488       |
| 36t37 | Manufacturing, nec           | 0.018       | 0.012       | 0.047        | 0.085      | 0.176       |
| 50t52 | Wholesale, Retail            | 0.024       | 0.014       | 0.042        | 0.016      | 0.072       |
| 55    | Hotels, Restaurant           | 0.0004      | 0.002       | 0.061        | 0.004      | 0.067       |
| 64    | Communications               | 0.069       | 0.207       | 0.013        | 0.023      | 0.043       |
| 65t67 | Financial services           | 0.182       | 0.104       | 0.041        | 0.009      | 0.023       |
| 71t74 | Business services            | 0.110       | 0.038       | 0.018        | NA         | 0.026       |
| 15t74 | TOTAL ECONOMY*               | 0.088       | 0.048       | 0.039        | 0.395      | 0.106       |

Notes: \*excludes real estate activities.

## V. RESULTS

### 5.1 Benchmark specification

We start our empirical analysis by estimating equation (4) under the assumption that our spillover proxies are uncorrelated with other external sources of companies' productivity performance. We will relax this assumption in Section 5.2. Obtaining consistent estimates of the input elasticities in equations (3) requires us to deal with two key econometric issues: cross sectional heterogeneity and endogeneity.<sup>12</sup> The former is addressed with the use of panel data methods (Fixed Effect estimator). To address the endogeneity problem we use the Generalised Method of Moments (GMM) estimator, where lagged values of the endogenous regressors are used as instruments for firm-level variables, under the assumption that productivity shocks at

time  $t$  are uncorrelated with input choices in previous periods. We limit the number of lags to three to avoid instrument proliferation and the associated upward bias in estimated coefficients (Roodman 2009). The validity of the instruments is assessed by the Kleibergen and Paap (2006) test of under-identification and the Hansen-J (1982) test of over-identifying restrictions. We also correct the covariance matrix for arbitrary heteroskedasticity and for the presence of first-order serial correlation.

**TABLE 3**

ICT Spillover and Absorptive Capacity

|  | (1)                 | (2)                  | (3)                  | (4)                  |
|--|---------------------|----------------------|----------------------|----------------------|
| <i>Company level variables</i>                   |                     |                      |                      |                      |
| Physical capital per worker ( $\beta$ )          | 0.122***<br>(0.026) | 0.114***<br>(0.026)  | 0.115***<br>(0.026)  | 0.114***<br>(0.026)  |
| R&D capital per worker ( $\gamma$ )              | 0.116***<br>(0.021) | 0.105***<br>(0.021)  | 0.0983***<br>(0.023) | 0.0986***<br>(0.022) |
| <i>Industry level variables and interactions</i> |                     |                      |                      |                      |
| Intra-industry ICT p.w. ( $\chi_1$ )             |                     | -0.322***<br>(0.038) | -0.403***<br>(0.046) | -0.390***<br>(0.044) |
| Firm R&D*intra-industry ICT p.w. ( $\eta_1$ )    |                     | 0.211***<br>(0.034)  | 0.016***<br>(0.006)  | 0.013***<br>(0.004)  |
| Inter-industry ICT p.w. ( $\chi_2$ )             |                     |                      | 0.211***<br>(0.035)  | 0.203***<br>(0.034)  |
| Firm R&D*inter-industry ICT p.w. ( $\eta_2$ )    |                     |                      | -0.002<br>(0.003)    |                      |
| Obs.   | 6,876               | 6,704                | 6,704                | 6,704                |
| R-squared  | 0.220               | 0.240                | 0.241                | 0.241                |
| No. of Firms                                     | 968                 | 938                  | 938                  | 938                  |
| Kleibergen-Paap LM statistic                     | <0.001              | <0.001               | <0.001               | <0.001               |
| P-value  |                     |                      |                      |                      |
| Hansen J test P-value                            | 0.191               | 0.170                | 0.212                | 0.264                |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. All variables are expressed in per worker terms. Standard errors robust to heteroskedasticity and first-order serial correlation are reported in parentheses. The dependent variable is labour productivity. All company level variables have been instrumented with their own values up to two-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%.

Table 3 reports the results of the estimation of equation (4). The first column does not include any spillover effects. Column (2) includes intra and inter-industry spillovers while columns (3) and (4) introduce the impact of absorptive capacity. In column (1) our estimates for the coefficients on physical and R&D capital per worker are consistent with prior knowledge of factor shares. Existing evidence on the R&D elasticity provides a range of values, from 0.04 (Griliches 1979, Bloom et al. 2013) to 0.18 (Griliches and Mairesse 1984), and our point estimate of 0.116 lies within this interval. We also tested the hypothesis of constant returns to scale (CRS) and we could not reject the null hypothesis of constant returns at the 5% significance level.<sup>13</sup> Importantly, these estimates are robust to the introduction of the spillover proxies.

Column (2) reveals that intra-industry spillovers have a negative and significant impact on productivity. These results are consistent with Stiroh (2002), for example, who finds that industry ICT capital is negatively related to TFP growth in US manufacturing industries. On the other hand, the coefficient estimate for the inter-industry effect is positive and statistically significant; this suggests that a 1% increase in ICT investment across all industries raises companies' productivity by approximately 0.2%. This effect is not trivial but it does not offset the negative impact from ICT investments within the company's own industry.

The pattern of results does not change if we consider each spillover variable individually. This implies that the two measures pick up different types of externalities, which affect productivity in opposite directions. The negative productivity effect from intra-industry ICT may be due to the fact that this variable is capturing a type of knowledge which is of a highly technical nature and whose adoption and implementation within the firm can be particularly costly (Cantner and Pyka 1998). In fact, related studies have shown that the new technology requires a re-

organization of the production process, which implies large adjustment costs for companies, particularly in the initial stage of diffusion (Bresnahan 2003, Kiley, 2001). The positive inter-industry effect, on the other hand, is likely to capture a type of knowledge that is of less technical nature and which requires fewer adjustments and/or investments in complementary capital. This could include, for example, improved interactions across firms, as discussed in Brynjolfsson et al. (2002). This is also consistent with evidence provided by Mun and Nadiri (2002) on the ability of information technology to enable productivity spillovers across US industries through supplier-customer transactions<sup>14</sup>.

Columns (3) and (4) present the estimation of our extended model, which accounts for the role of firms' absorptive capacity. This phenomenon is captured by the introduction of an interaction term between companies' R&D and the two spillover proxies, as described in Equation (5). In column (3) the coefficient estimate of the interaction between R&D and intra-industry ICT is positive and significant, confirming the mutually self-enforcing effect of firm's innovative effort and intra-industry ICT capital. However, when considering the inter-industry spillover we do not find any significant role for absorptive capacity as the interaction term is not statistically significant. Inter-industry knowledge has a positive impact on productivity without requiring the firm's specific effort. This supports our previous interpretation related to the more easy implementation and adoption of knowledge associated with the inter-industry spillover. As Cohen and Levinthal (1990) point out, when learning is less demanding *"a firm's own R&D has little impact on its absorptive capacity. In the extreme case in which external knowledge can be assimilated without any specialized expertise, a firm's own R&D would have no effect on its absorptive capacity"*. In the reminder of our analysis we will only include the

interaction between own-company R&D and intra-industry ICT spillovers, i.e. we will carry on with the specification presented in column 4.

Our results show that firms' investments in R&D promote the absorption of knowledge more directly related to firm production. However, given the negative sign of the intra industry spillover coefficient, it is still unclear whether this external knowledge has an overall positive effect on productivity, i.e. to what extent absorptive capacity is turning external knowledge into productivity gains. Table 4 provides the answer this question. Following the discussion in Section 3, we compute the total intra-industry spillover evaluating the interaction effect (absorptive capacity) at different points of the companies' R&D distribution. Despite the positive coefficient of the interaction term, the total intra-industry spillover effect remains negative, although decreasing with the size of the firm's knowledge base. The total spillover effect from ICT, given by the sum of total intra- and inter-industry effects is negative for all companies.

**Table 4**

Total ICT Spillover Effect

|                  | <b>Percentile</b>                                  | <b>1%</b> | <b>5%</b> | <b>10%</b> | <b>25%</b> | <b>50%</b> | <b>75%</b> | <b>90%</b> | <b>95%</b> | <b>99%</b> |
|------------------|--|-----------|-----------|------------|------------|------------|------------|------------|------------|------------|
|                  | <i>Ln(R&amp;D)</i>                                 | 0.59      | 1.51      | 2.09       | 3.24       | 4.32       | 5.42       | 6.80       | 7.85       | 9.27       |
| <i>a</i>         | <i>AC- <math>\eta_1 \cdot \ln(R\&amp;D)</math></i> | 0.01      | 0.02      | 0.03       | 0.04       | 0.06       | 0.07       | 0.09       | 0.10       | 0.12       |
| <i>b</i>         | <i>Intra-industry (<math>\chi_1</math>)</i>        | -0.39     | -0.39     | -0.39      | -0.39      | -0.39      | -0.39      | -0.39      | -0.39      | -0.39      |
| <i>c=a+b</i>     | <i>Total Intra industry</i>                        | -0.38     | -0.37     | -0.36      | -0.35      | -0.33      | -0.32      | -0.30      | -0.29      | -0.27      |
| <i>d</i>         | <i>Inter industry (<math>\chi_2</math>)</i>        | 0.20      | 0.20      | 0.20       | 0.20       | 0.20       | 0.20       | 0.20       | 0.20       | 0.20       |
| <i>c+d</i>       | <i>Total spill</i>                                 | -0.18     | -0.17     | -0.16      | -0.15      | -0.13      | -0.12      | -0.1       | -0.09      | -0.07      |
| <i>H0: c+d=0</i> | <i>P-value</i>                                     | [0.00]    | [0.00]    | [0.00]     | [0.00]     | [0.01]     | [0.02]     | [0.04]     | [0.08]     | [0.17]     |

Notes: computations based on the results in Table 3, column 4. AC: absorptive capacity term

In the last row of table 4 we report the probability value for the test of the null hypothesis that the sum of the total intra and inter-industry spillover equals zero, under the alternative that the sum of the two effects is negative. We reject the null



hypothesis for all companies up to the 90th percentile of the R&D distribution. For the five percent of firms with the most R&D stocks the point estimate of total spillovers is negative but not significantly different from zero. In other words, at the outset of the information age, the negative effects of ICT associated with restructuring appear to prevail for a typical US company. Only those companies with higher absorptive capacity are able to off-set this negative effect.

## 5.2. Identification of the spillover effect

**The identification of ICT spillover effects is particularly challenging as industry-level variables may pick up other factors not included in our model. In particular, the possible relationship between ICT at the industry level and companies' productivity could be the result of exogenous industry-specific technical change rather than a pure spillover effect.** For example, when a new technology is introduced in a particular industry, a firm adopting this technology can experience an increase in productivity. This effect could be captured by our ICT proxies and erroneously interpreted as a spillover.

To avoid this problem and to correctly identify the spillover effect, we follow a dual strategy. First, we introduce measures of R&D at the industry level so any spillover effect will be net of other industry-specific endogenous technological innovation<sup>15</sup>. Additionally, this variable will control for R&D-based knowledge spillovers, whose effect could also be confounded with spillovers from ICT (Acharya 2016). Results are presented in Table 5. In column 1, we find a positive effect of intra-industry R&D capital, while the ICT spillover impact on productivity is still strong and significant. In column 2 we conduct a further robustness check for the ICT spillover effect by including the total number of hours worked in our specification. This variable controls for changes in labour utilization over the business cycle, whose

effect could be picked up by our spillover proxies. For example, Oliner et al. (2008) suggest that the resurgence in labour productivity in the 1990s could have been caused by normal cyclical dynamics.<sup>16</sup> The coefficient on the total number of hours worked is positive and statistically significant, confirming the cyclical nature of productivity movements; however, its inclusion does not alter the pattern of our results.<sup>17</sup>

Second, we follow Bloom et al. (2013) in implementing a two-stage instrumental variable approach. The first-stage consists in regressing ICT capital per worker on the OECD index of regulation of the telecom service industry (*regtel*), and a set of industry and time dummies ( $a_j$  and  $d_t$ ), as follows:

$$ictl_{jt} = a_j + regtel_t + \sum_{t=1}^{10} \delta d_t + \varepsilon_{jt} \quad (6)$$

where *regtel* is the OECD index of regulation on telecom services (in logs), which measures the strictness of regulation in the US telecom service industry<sup>18</sup>. Our instrument choice relies on the fact that lower administrative barriers in the telecom sector would contribute to a larger supply of digital service inputs and therefore to an increasing demand for complementary assets, such as computers and other communication devices. The faster liberalization of the US telecom market during the 1990s may have favored the adoption of new digital technologies as these assets have been increasingly dependent on the provision of Internet services. This implies a strong correlation between our instrument and the stock of ICT at the industry level. At the same time, the regulation indicator results from a long-lasting political decision making process, which can be considered as predetermined with respect to firms' investment choices. Hence, we rule out the possibility that the ICT spillover variables capture the endogenous adoption of the new technology. In the second stage, we

replace actual ICT in equation (5) with its fitted values, re-constructing both the un-weighted and the weighted ICT spillover measures.

**TABLE 5**

| Identification of the ICT Spillover           |  |                      |                                  |                      |
|---|--|----------------------|----------------------------------|----------------------|
|   | (1)  | (2)                  | (3)                              | (4)                  |
|   | <i>Exogenous ICT spillovers</i>                  |                      | <i>Endogenous ICT spillovers</i> |                      |
|   | <i>Company level variables</i>                   |                      |                                  |                      |
| Physical capital per worker ( $\beta$ )       | 0.115***<br>(0.029)                              | 0.116***<br>(0.026)  | 0.119***<br>(0.034)              | 0.123***<br>(0.030)  |
| R&D capital per worker ( $\gamma$ )           | 0.092***<br>(0.024)                              | 0.100***<br>(0.022)  | 0.111***<br>(0.027)              | 0.116***<br>(0.025)  |
|   | <i>Industry level variables and interactions</i> |                      |                                  |                      |
| Intra-industry ICT p.w. ( $\chi_1$ )          | -0.497***<br>(0.057)                             | -0.428***<br>(0.045) | -0.423***<br>(0.010)             | -0.514***<br>(0.107) |
| Firm R&D*intra-industry ICT p.w. ( $\eta_1$ ) | 0.014***<br>(0.004)                              | 0.012***<br>(0.004)  | 0.012**<br>(0.005)               | 0.009**<br>(0.005)   |
| Inter-industry ICT p.w. ( $\chi_2$ )          | 0.209***<br>(0.037)                              | 0.221***<br>(0.035)  | 0.197***<br>(0.042)              | 0.216***<br>(0.041)  |
| Intra-industry R&D p. w. ( $\phi_1$ )         | 0.046**<br>(0.018)                               |                      | -0.001<br>(0.021)                |                      |
| Hours worked ( $\rho$ )                       |  | 0.214**<br>(0.088)   |                                  | -0.121<br>(0.100)    |
| <i>First-stage IV</i>                         |  |                      |                                  |                      |
| <i>Coefficient (regtel)</i>                   |  |                      |                                  | -0.94                |
| <i>F-test</i>                                 |  |                      |                                  | 755.2                |
| Obs.  | 5,814  | 6,704                | 4,982                            | 5,689                |
| R-squared                                     | 0.257  | 0.243                | 0.228                            | 0.208                |
| No. of Firms                                  | 785  | 938                  | 755                              | 886                  |
| Kleibergen-Paap LM test P-value               | <0.001   | <0.001               | <0.001                           | <0.001               |
| Hansen J test P-value                         | 0.395  | 0.285                | 0.475                            | 0.369                |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. All variables are expressed in per worker terms. Standard errors robust to heteroskedasticity and first-order serial correlation are reported in parentheses. The dependent variable is labour productivity. All company level variables have been instrumented with their own values up to two-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%.

The second stage coefficients are presented in columns (3) and (4). Results regarding the ICT spillover effects are consistent with previous estimates. This means that our ICT industry variables are indeed capturing a true spillover effect and not, for example, the impact of other un-observed technological factors.<sup>19</sup> Table 5 also shows the first stage coefficient on our instrumental variable (*regtel*). This coefficient is statistically significant at the 1% significance level and the F test confirms the validity of our instrument.<sup>20</sup>

In the rest of the paper we will relax the assumption of endogenous ICT spillovers while investigating the 'delayed effects' hypothesis for industry ICT. To test

this hypothesis we rely on the use of lagged values of the ICT proxies, which should mitigate any remaining endogeneity issues in the light of the fact that, at the industry level, past ICT investments are not influenced by firms' expectations of future sales.

### 5.3 The lagged effect of ICT spillovers

So far we have only considered the contemporaneous influence of both ICT spillovers and absorptive capacity. This does not account for the presence of lagged effects, an issue that has been discussed in the literature but not often tested. As mentioned in Section 2, the GPT view stresses how the impact of ICT, or any other major technological innovation, can be delayed while the necessary complementary investments are put in place (Brynjolfsson and Hitt 2003). Extending this argument to ICT spillovers, lagged rather than contemporaneous spillovers should have a stronger impact on productivity performance. On the other hand, Moshiri and Simpson (2011) discuss the possibility that network effects related to ICT may decrease over time or even disappear when the majority of firms have joined the network. As for absorptive capacity the literature has discussed the possibility that its impact might change over time but the direction of this change is not known.

To investigate these issues, we re-estimate equation (5) considering the impact of spillovers and absorptive capacity with 1, 3 and 5 year lags. Results are presented in the first three columns of Table 6. In columns 4-6, we control for the impact of R&D at the industry level, following the same lag structure. Results change dramatically when we consider different lags of the spillover variables. At time  $t-1$  we still have a negative intra-industry ICT spillover and a positive inter-industry effect. The former is still negative, but of smaller magnitude, at time  $t-3$ . As a result, the overall spillover effect is positive. However, when we consider the 5-year lag specification both intra- and inter-industry effects of information technology are

positive and significant. These results are robust to the introduction of R&D at the industry level (columns 4-6), although the inter-industry variable has a weaker effect in the 5-year lag specification (column 6).<sup>21</sup>

**TABLE 6**  
**Lagged ICT Spillovers and Companies' Productivity Performance**

|  | (1)                  | (2)                  | (3)                 | (4)                  | (5)                 | (6)                 |
|--|----------------------|----------------------|---------------------|----------------------|---------------------|---------------------|
|  | <i>1-year lag</i>    | <i>3-year lag</i>    | <i>5-year lag</i>   | <i>1-year lag</i>    | <i>3-year lag</i>   | <i>5-year lag</i>   |
| <i>Company level variables</i>                   |                      |                      |                     |                      |                     |                     |
| Physical capital per worker ( $\beta$ )          | 0.119***<br>(0.026)  | 0.111***<br>(0.030)  | 0.048<br>(0.048)    | 0.117***<br>(0.029)  | 0.105***<br>(0.034) | 0.040<br>(0.053)    |
| R&D capital per worker ( $\gamma$ )              | 0.097***<br>(0.022)  | 0.112***<br>(0.025)  | 0.113***<br>(0.038) | 0.090***<br>(0.024)  | 0.106***<br>(0.027) | 0.119***<br>(0.041) |
| <i>Industry level variables and interactions</i> |                      |                      |                     |                      |                     |                     |
| Intra-industry ICT p.w. ( $\chi_1$ )             | -0.416***<br>(0.046) | -0.198***<br>(0.060) | 0.266***<br>(0.095) | -0.475***<br>(0.059) | -0.155**<br>(0.069) | 0.244**<br>(0.104)  |
| Firm R&D*intra-industry ICT p.w. ( $\eta_1$ )    | 0.015***<br>(0.004)  | 0.013***<br>(0.005)  | -0.007<br>(0.009)   | 0.017***<br>(0.004)  | 0.016***<br>(0.005) | -0.005<br>(0.009)   |
| Inter-industry ICT p.w. ( $\chi_2$ )             | 0.194***<br>(0.033)  | 0.236***<br>(0.036)  | 0.174***<br>(0.044) | 0.176***<br>(0.035)  | 0.161***<br>(0.041) | 0.0844*<br>(0.047)  |
| Intra-industry R&D p.w. ( $\phi_1$ )             |                      |                      |                     | 0.036**<br>(0.018)   | -0.014<br>(0.021)   | -0.052<br>(0.034)   |
| Obs.   | 6,704                | 5,893                | 4,049               | 5,814                | 5,128               | 3,616               |
| R-squared  | 0.241                | 0.205                | 0.155               | 0.256                | 0.217               | 0.170               |
| No. of Firms                                     | 938                  | 915                  | 816                 | 785                  | 770                 | 708                 |
| Kleibergen-Paap LM test P-value                  | <0.001               | <0.001               | <0.001              | <0.001               | <0.001              | <0.001              |
| Hansen J test P-value                            | 0.274                | 0.254                | 0.515               | 0.374                | 0.375               | 0.652               |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. All variables are expressed in per worker terms. Standard errors robust to heteroskedasticity and first-order serial correlation are reported in parentheses. The dependent variable is labour productivity. All company level variables have been instrumented with their own values up to two-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%.

**The pattern that emerges from our estimation is consistent with the GPT analysis, which shows that learning costs are particularly steep in the initial phase because the adoption and implementation of a new technology requires high levels of skills and other complementary resources (Greenwood and Yorukoglu 1997). A drop in productivity and an increase in the skill premium are common in this initial phase (Jovanovich and Rousseau 2005). However, over time, as the technology becomes more accessible, the skill premium declines and the learning curve tapers off, allowing companies to reap the benefits from the initial investment. Similarly, our estimates indicate that returns to ICT spillovers**

increase more than proportionally at later stages of the ICT diffusion, as the learning costs decline and the technology approaches maturity.<sup>22</sup>

Consistent with this argument, we find that, in the 5-year lag specification, spillovers are not affected by companies' knowledge base and absorptive capacity<sup>23</sup>. In fact the absorptive capacity term is no longer statistically significant. This implies that, over time, the increasing investments in R&D are no longer necessary to benefit from the ICT-related external knowledge, either because the company has already accumulated a substantial amount of internal competencies, or because the technology has become more established and less costly to assimilate and to turn into productivity gains<sup>24</sup>. Hence, our results suggest that while the adoption phase of a new technology requires substantial absorptive capacity, over time the role of absorptive capacity diminishes.<sup>25</sup>

Results in table 6 also show that the coefficient on the R&D spillover variable is statistically significant only at time  $t-1$ . This suggests that the effects of R&D and ICT spillovers on companies' productivity materialize at different points in time. This excludes the possibility that the effect of ICT somehow captures un-measured complementary factors such as intangible or organizational assets, contradicting the argument put forward by Acharya (2016)<sup>26</sup>.

Overall, our analysis shows that all companies gain positive and significant productivity spillovers from industry ICT with a 3 to 5-year lag. The total impact is not trivial: a 1% increase in industry ICT increases companies' productivity by approximately 0.2-0.3%. **This is a sizeable effect compared to what has been found in the literature so far. For example, in Brynjolfsson and Hitt (2003) the within firm ICT spillover effect ranges between 0.06 and 0.10, while Hitt and Tambe (2014) estimate an ICT spillover effect of 0.01-0.02**

**Our estimated spillover effect, associated with the diffusion of ICT at the industry level, is comparable in size with spillovers from R&D found in several earlier studies (Frantzen 2002, Guellec and Van Potterlsberghe 2004, Franco et al. 2016). This may indicate that industry R&D spillovers might have been overstated in earlier contributions as they do not account for the externalities induced by the diffusion of ICT (Venturini 2015).**

**Finally, one may question whether our industry variables capture returns to firm's own investment in ICT, given that our dataset does not allow us to distinguish firm ICT assets from its total capital. Cordona et al. (2013) review several empirical papers on ICT and productivity and they show that the estimated internal returns to ICT in the US range between 0.021 and 0.098. This means that the size of our spillover effect is too high to capture exclusively internal returns.**

Our results are also robust to an array of sensitivity checks. First, we investigate whether alternative weighting schemes for the inter-industry ICT spillovers could affect our coefficient estimates. We construct inter-industry measures based on the relative trade size of the recipient sector, as in Coe and Helpman (1995), and using information on inter-industry patent citations to trace potential spillover flows. The latter control for the technology distance between pairs of industries and therefore may better capture the ability of the firm in the receiving industry to assimilate technological externalities associated with the ICT usage in surrounding sectors. Details on variable constructions and table of results are presented in Appendix B, Table B.1. Results based on these alternative weighting schemes are still characterized by the same pattern discussed above.

As additional sensitivity tests, we check whether our coefficient estimates might be affected by company characteristics. We remove large firms in terms of sales and R&D expenses (the top 5% performing companies) from the sample to check whether their presence might drive our spillover and absorptive capacity effects. Results, presented in Appendix Table B.2 show that our conclusions remains, indicating that the spillover effect associated with the arrival of the new technology is not specific to larger companies but is a distinguishing characteristic of those tasks building the base of absorptive capacity (represented in our case by R&D activities). We also investigated whether our findings are due to the sample composition and hence we re-estimated our model using a balanced sample, but this did not change our main conclusions regarding the spillover effect. Finally, we examine whether our results are driven by some specific industry patterns. We therefore run our key specifications distinguishing between ICT-producing and ICT-using industries - see appendix table B.3. In this case, the contemporaneous effect of both types of ICT spillover is confirmed though their lagged impacts are not statistically significant, probably due to the reduced sample size.

## VII. CONCLUSIONS

Earlier work has often questioned the presence of ICT spillover in the US and, more generally, in all industrialized economies (Kretschmer 2012). Results of these studies are often ambiguous and inconclusive. In this paper we have broadened the scope of the analysis, highlighting the importance of external knowledge that the company acquires through market transactions and that is captured by the ICT spillover effect. Our findings show that whilst ICT



investment in upstream or downstream industries lead to a contemporaneous positive effect on productivity, the ICT diffusion in the market where the firm operates is initially detrimental for its productivity levels. Hence, at the beginning of the 1990s the negative spillover effects prevails, with the exception of those companies at the top end of the R&D distribution, i.e. those companies with a higher absorptive capacity. This is the first paper to assess the importance of absorptive capacity in the US, in relation to ICT spillovers.

When we account for a delayed impact, we find that all companies benefit from ICT spillovers. After a three-year lag, the intra-industry spillover is still negative but the increase in the inter-industry effect means that the overall spillover positively affects productivity. After five years, both intra and inter-industry effects are positive. This is consistent with studies who find increasing returns to firms' investment in ICT over time (Bresnahan, Brynjolfsson and Hitt 2002) and, to our knowledge, our paper is the first to provide an empirical estimate of the length of time necessary for ICT spillovers to increase productivity levels.

Another new result, which differs from previous work, is that the complementarity between firm-level R&D and industry ICT decreases over time and becomes insignificant after five years. A possible reason is that the learning process associated with ICT is complex and, at the beginning, only firms beyond a given threshold of technological capabilities (skills, R&D, etc.) are able to handle the complex changes induced by the new technology. Once learning about the implementation of the new technology improves, absorptive capacity is no longer relevant to assimilate external knowledge and a large number of firms gain from these spillovers. An alternative but not competitive explanation is that

**over time the technology has become more codified and easier to use and less demanding in terms of additional investments in absorptive capacity (Bartel and Lichtenberg, 1987, Chun, 2003 and Robinson et al. 2008).**

Overall our study provides strong support for the presence of spillover effects in the US economy and suggests that ICT spillovers have been one of the driving factors behind the 1990s US productivity revival. It is perhaps the lack of such spillovers in Europe one of the reasons behind the US-EU productivity gap, i.e. one of the main objects of research on ICT in the latest years (Nicoletti and Scarpetta, 2003, Inklaar et al. 2008).

Our work also opens new avenues for future research. We have focused on firms that actively engage in R&D; however, firms that do not invest in formal R&D could still take advantage of ICT spillovers. Testing this hypothesis requires the construction of different measures of absorptive capacity that rely, for example, on managerial and organizational efforts, rather than research effort. Additional questions to address are whether the spillover effect persists in more recent years, and to what extent other countries have been able to enjoy the benefit of ICT-related external knowledge.

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## Appendix A

Table A.1

Test for cross sectional dependence in the firm-level data (Pesaran 2004)

| Variable                    | CD- test | p-value |
|-----------------------------|----------|---------|
| Labor productivity          | 310.36   | <0.001  |
| Physical capital per worker | 93.9     | <0.001  |
| R&D capital per worker      | 165.25   | <0.001  |

Notes: the test is based on the null hypothesis of cross-section independence

## Appendix B: robustness checks

This section reports some additional robustness checks for the key results of Table 6, based on alternative weighting schemes for the inter-industry ICT spillover variable. In our main set of results the weighting factor was given by the ratio between intermediate transactions among industries  $j$  and  $f$  ( $M_{jft}$ ) and total intermediates' sales of the selling industry ( $Y_{ft}$ ) - see equation (2). Alternatively, we can construct a weighting factor by dividing inter-industry intermediate transactions by the total intermediate purchases of the buying industry ( $P_{jt}$ ). We call this measure  $wICT_{jt}^b$ , where 'b' stands for 'buyer':

$$wICTL_{jt}^b = \sum_{j=1}^{17} w_{jft}^b \times ICTL_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{P_{jt}} \times ICTL_{ft} \quad (B.1)$$

Results based on this measure are presented in cols. (1) and (2) of Table B.2. These estimates broadly confirm our baseline findings, even though the inter-industry ICT spillover appears somewhat higher.

We also test the robustness of our results to the use of a weighting scheme based on inter-industry patent citations. Indeed, one may question that the ability to exploit technology improvements of the surrounding industries may depend on technological proximity of sectors, rather than the intensity of their trade transactions. For this reason, we build inter-industry patent citation matrix flows using NBER

USPTO patent data files 2006 (see Hall et al. 2001 for details). We consider two versions of this patent based ICT spillover measure (denoted by ‘p’), following the two alternative weighting methodologies shown above. In equation (B.2), the weighting factor ( $w_{jft}^p$ ) is the ratio between the citations made by patent assignees operating in industry  $j$  to patents applied for firms operating in industry  $f$  ( $C_{jft}$ ) and total (backward) citations made by industry  $j$  ( $C_{jt}$ ):

$$wICTL_{jt}^p = \sum_{j=1}^{12} w_{jft}^p \times ICTL_{ft} = \sum_{j=1}^{12} \frac{C_{jft}}{C_{jt}} \times ICTL_{ft}. \quad (B.2)$$

In equation (B.3) the weighting factor is scaled by the total (forward) citations received by industry  $f$  ( $C_{ft}$ ):

$$wICTL_{jt}^{p,b} = \sum_{j=1}^{12} w_{jft}^{p,b} \times ICTL_{ft} = \sum_{j=1}^{12} \frac{C_{jft}}{C_{ft}} \times ICTL_{ft}. \quad (B.3)$$

Equation (B.2) defines the inter-industry ICT spillover variable using weights reflecting the total amount of knowledge “released” by contiguous industries ( $wICT_{jt}^b$ ). Equation (B.3) considers as a scale factor the total amount of knowledge “acquired” by the recipient industry  $wICT_{jt}^{p,b}$ . Results based on these patent-weighted measures of spillovers are presented in columns 3-6 of Table A.1. These only refer to the manufacturing sector as there is no information on patents for services.

**TABLE B.1**  
**Robustness Checks for the Extended Production**  
**Function Based on Alternative Weighting Schemes**

| Weighting scheme                                 | <i>All</i><br>I-O transactions<br>on total intermediate purchases<br>(A.1) |                       | <i>Manufacturing</i><br>Total backward<br>patent citations scaled on cited<br>industry<br>(A.2) |                       | <i>Manufacturing</i><br>Total backward<br>patent citations scaled on citing<br>industry<br>(A.3) |                       |
|--|--|-----------------------|---|-----------------------|--|-----------------------|
|  | (1)  | (2)                   | (3)   | (4)                   | (5)  | (6)                   |
|  | <i>Contempo-<br/>raneous</i>   | <i>5-year lag</i>     | <i>Contempo-<br/>raneous</i>  | <i>5-year lag</i>     | <i>Contempo-<br/>raneous</i>   | <i>5-year<br/>lag</i> |
| <i>Company level variables</i>                   |  |                       |   |                       |  |                       |
| Physical capital p.w.                            | 0.111***<br>(0.0291)   | 0.0365<br>(0.0540)    | 0.119***<br>(0.0297)  | 0.0381<br>(0.0548)    | 0.117***<br>(0.0297)   | 0.0399<br>(0.0547)    |
| R&D capital p.w.                                 | 0.105***<br>(0.0236)   | 0.122***<br>(0.0403)  | 0.0992***<br>(0.0242)   | 0.122***<br>(0.0406)  | 0.0928***<br>(0.0241)  | 0.121***<br>(0.0407)  |
| <i>Industry level variables and interactions</i> |  |                       |   |                       |  |                       |
| Intra-industry ICT<br>( $\chi_1$ )               | -0.409***<br>(0.0575)  | 0.262**<br>(0.105)    | -0.388***<br>(0.0636)   | 0.263**<br>(0.106)    | -0.244***<br>(0.0623)  | 0.267**<br>(0.106)    |
| Firm R&D*intra-<br>industry ICT ( $\eta_1$ )     | 0.0126***<br>(0.00440)   | -0.00581<br>(0.00915) | 0.0145***<br>(0.00436)  | -0.00423<br>(0.00917) | 0.0147***<br>(0.00425)   | -0.00495<br>(0.00916) |
| Inter-industry ICT<br>( $\chi_2$ )               | 0.509***<br>(0.105)  | 0.0536<br>(0.109)     | 0.432***<br>(0.123)   | 0.366***<br>(0.117)   | 0.387***<br>(0.0525)   | 0.199***<br>(0.0451)  |
| Intra-industry R&D<br>( $\phi_1$ )               | 0.0340<br>(0.0222)   | -0.0631*<br>(0.0343)  | 0.0777**<br>(0.0327)  | -0.0601<br>(0.0432)   | 0.0717**<br>(0.0323)   | -0.0936**<br>(0.0466) |
| Obs.   | 5,814  | 3,616                 | 5,680   | 3,545                 | 5,680  | 3,545                 |
| R-squared  | 0.258  | 0.169                 | 0.253   | 0.174                 | 0.259  | 0.176                 |
| No. of Firms                                     | 785  | 708                   | 761   | 692                   | 761  | 692                   |
| Kleibergen-Paap LM<br>test P-value               | <0.001   | <0.001                | <0.001  | <0.001                | <0.001   | <0.001                |
| Hansen J test P-value                            | 0.392  | 0.620                 | 0.460   | 0.580                 | 0.511  | 0.625                 |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. All variables are expressed in per worker terms. Standard errors robust to heteroskedasticity and first-order serial correlation are reported in parentheses. The dependent variable is labour productivity. All company level variables have been instrumented with their own values up to two-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%.



Tables B.2 and B.3 presents results for the additional sensitivity tests, discussed in section 5.2. As additional sensitivity tests, we remove large firms in terms of sales and R&D expenses (the top 5% performing companies) from the sample to check whether their presence might drive our results. Our main conclusions remain unchallenged (see Table B.2). Finally, we investigate whether our results are driven by some specific industry patterns. We therefore run our key specifications distinguishing between ICT-producing and ICT-using industries. In this case, the contemporaneous effect of both types of ICT spillover is confirmed while their lagged impacts are not statistically significant, probably due to the very small sample size (see Table B.3).

**TABLE B.2**  
Excluding large firms

|  | <i>Top 5% performers<br/>R&amp;D capital</i> |                      | <i>Top 5% performers<br/>Total Sales</i> |                      |
|--|--|----------------------|--|----------------------|
|  | (1)  | (2)                  | (3)                                      | (4)                  |
|  | <i>Contempo-<br/>raneous</i>                 | <i>5-year lag</i>    | <i>Contempo-<br/>raneous</i>             | <i>5-year lag</i>    |
| <i>Company level variables</i>                   |  |                      |  |                      |
| Physical capital p.w.                            | 0.108***<br>(0.0300)                         | 0.0286<br>(0.0567)   | 0.109***<br>(0.0300)                     | 0.0259<br>(0.0570)   |
| R&D capital p.w.                                 | 0.0920***<br>(0.0246)                        | 0.113***<br>(0.0420) | 0.0932***<br>(0.0249)                    | 0.114***<br>(0.0426) |
| <i>Industry level variables and interactions</i> |  |                      |  |                      |
| Intra-industry ICT ( $\chi_1$ )                  | -0.484***<br>(0.0593)                        | 0.287**<br>(0.117)   | -0.496***<br>(0.0605)                    | 0.292**<br>(0.119)   |
| Firm R&D*intra-industry ICT ( $\eta_1$ )         | 0.0133**<br>(0.00550)                        | -0.00828<br>(0.0127) | 0.0103**<br>(0.00517)                    | -0.0127<br>(0.0120)  |
| Inter-industry ICT ( $\chi_2$ )                  | 0.212***<br>(0.0397)                         | 0.0813*<br>(0.0491)  | 0.210***<br>(0.0413)                     | 0.0774<br>(0.0503)   |
| Intra-industry R&D ( $\phi_1$ )                  | 0.0464**<br>(0.0186)                         | -0.0374<br>(0.0347)  | 0.0536**<br>(0.0228)                     | -0.0428<br>(0.0399)  |
| Obs.   | 5,478  | 3,373                | 5,479                                    | 3,366                |
| R-squared  | 0.247  | 0.162                | 0.248                                    | 0.161                |
| No. of Firms                                     | 752  | 672                  | 758                                      | 671                  |
| Kleibergen-Paap LM test P-value                  | <0.001                                       | <0.001               | <0.001                                   | <0.001               |
| Hansen J test P-value                            | 0.564  | 0.600                | 0.466                                    | 0.534                |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. All variables are expressed in per worker terms. Standard errors robust to heteroskedasticity and first-order serial correlation are reported in parentheses. The dependent variable is labour productivity. All company level variables have been instrumented with their own values up to two-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%.

**TABLE B.3**  
Distinguishing between ICT producers/users

|  | <i>ICT producers</i><br>(ISIC 30t33, 64) |                      | <i>ICT users</i><br>(ISIC 17t19, 21t22, 29, 34t35, 36t37, 50t52, 65t67, 71t74) |                   |
|--|--|----------------------|--|-------------------|
|  | (1)                                      | (2)                  | (3)  | (4)               |
|  | <i>Contempo-<br/>raneous</i>             | <i>5-year lag</i>    | <i>Contempo-<br/>raneous</i>   | <i>5-year lag</i> |
| <i>Company level variables</i>                   |  |                      |  |                   |
| Physical capital p.w.                            | 0.130***<br>(0.038)                      | 0.019<br>(0.072)     | 0.105**<br>(0.042)   | 0.132<br>(0.097)  |
| R&D capital p.w.                                 | 0.149***<br>(0.036)                      | 0.201***<br>(0.065)  | 0.053*<br>(0.032)  | 0.001<br>(0.0592) |
| <i>Industry level variables and interactions</i> |  |                      |  |                   |
| Intra-industry ICT ( $\chi_1$ )                  | -1.814*<br>(1.015)                       | -4.997*<br>(2.806)   | -0.230***<br>(0.072)   | -0.130<br>(0.130) |
| Firm R&D*intra-industry ICT ( $\eta_1$ )         | 0.031***<br>(0.008)                      | -0.002<br>(0.016)    | 0.003<br>(0.005)   | 0.014<br>(0.011)  |
| Inter-industry ICT ( $\chi_2$ )                  | 0.493<br>(0.953)                         | 4.816*<br>(2.841)    | -0.087<br>(0.055)  | -0.073<br>(0.058) |
| Intra-industry R&D ( $\phi_1$ )                  | -0.424<br>(0.290)                        | -0.653***<br>(0.201) | 0.019<br>(0.027)   | -0.027<br>(0.043) |
| Obs.   | 2,683                                    | 1,664                | 1,847  | 1,144             |
| R-squared  | 0.381                                    | 0.255                | 0.210  | 0.120             |
| No. of Firms                                     | 366                                      | 333                  | 247  | 219               |
| Kleibergen-Paap LM test P-value                  | <0.001                                   | <0.001               | <0.001   | <0.001            |
| Hansen J test P-value                            | 0.926                                    | 0.872                | 0.0327   | 0.00553           |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. All variables are expressed in per worker terms. Standard errors robust to heteroskedasticity and first-order serial correlation are reported in parentheses. The dependent variable is labour productivity. All company level variables have been instrumented with their own values up to two-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%.

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<sup>1</sup> Biagi (2013) provides another recent survey of the literature.

<sup>2</sup> One form of spillovers is related to the rapid decline in quality adjusted ICT prices, which has contributed to productivity growth. However, this 'pecuniary externality' cannot be considered as pure spillovers because it does not capture a transfer of knowledge but it results from an incorrect measure of capital equipment, materials and their prices (Stiroh 2002). The substantial productivity gains that firms would enjoy following a cost reduction are short lived with no implications for long-run growth.

<sup>3</sup> Basu and Fernald (2007) is to our knowledge the only study that finds some positive ICT spillovers in the US economy using industry level data. The positive effect is estimated only for lagged ICT, while the contemporaneous effect is negative.

<sup>4</sup> The hypothesis that the effect of spillovers depends on facilitating factors in the receiving firms or industries have already been investigated in relation to R&D and human capital (Griffith et al. 2004, Vandenbussche et al. 2006). There is also an extensive literature investigating the role of absorptive capacity in knowledge or technology transfers. See also Cohen and Levinthal (1989) and Yasar (2010).

<sup>5</sup> See, for example, Atrostic and Nguyen (2005), Moshiri and Simpson (2011).

<sup>6</sup> **For example, Greenwood and Yorokoglu (1997) discuss the macroeconomic implications of the learning process associated with ICT during the US productivity slowdown in the early 1970s. They argue that skills, which are a component of absorptive capacity, are particularly important in early phases of the diffusion of the new technology. Over time, the skill impact diminishes as learning becomes easier..**

<sup>7</sup> **Note that ICT is an industry level variable and it is divided by industry employment.**

<sup>8</sup> Several contributions claim that weighted measures of the pool of external knowledge are better spillover proxies as the weights capture the degree of 'closeness' between firms, expressed as 'technological' distance (Jaffe 1986), the extent of product market proximity (Bloom et al. 2013) or geographical distance (Lychagin et al. 2010). The weighting technique adopted here accounts for linkages between suppliers and customers, as in Mun and Nadiri (2002). Alternative weighting schemes, based on inter-industry patent citations, are considered in Appendix B.

<sup>9</sup> For example, Brynjolfsson et al. (2002) compute ICT capital using CII (Computer Intelligence Infocorp) data on computer hardware inventories and they state that 'The CII data provides a relatively narrow definition of computers that omits software, information system staff and telecommunication equipment'. Similar shortcomings of this data set are discussed in Draca et al. (2007).

<sup>10</sup> Zahra and George (2002) distinguish between potential and realized absorptive capacity. The first has to do with the two dimensions of acquisition and assimilation of knowledge. Realized absorptive capacity is related to the transformation and the exploitation of knowledge to commercial purposes. This is the aspect that has attracted several empirical contributions. We believe that the accumulation of R&D serves both purposes. In fact, not all investments in R&D lead to innovations but they increase the potentials to recognize and assimilate new knowledge, i.e. increase potential absorptive capacity.

<sup>11</sup> [http://niesr.ac.uk/sites/default/files/publications/dp416\\_0.pdf](http://niesr.ac.uk/sites/default/files/publications/dp416_0.pdf)

<sup>12</sup> **Cross-sectional dependence (CSD) is another source of bias. In fact, the Pesaran (2004) test for CSD rejects the null hypothesis of cross-sectional independence, as documented in Appendix table A.1. We control for CSD with the inclusion of time dummies, assuming homogenous factor loading across firms (Eberhardt et al. 2013). Other solutions for this problem are the use of the Driscoll-Kraay (1998) estimation methods or the implementation of the Common Correlated Effect (CCE) estimator (Pesaran 2006). These techniques rely on panels with long time series and relatively small cross section dimensions. Our panel, however, is characterized by a large number of cross-sectional units and a relatively short time dimension, which prevents us from applying these techniques.**

<sup>13</sup> **To test for the presence of constant returns to scale (CRS) we estimated the specification presented in column 1 adding employment as an additional regressor. Under the hypothesis of CRS the employment coefficient should not be statistically significant. We could not reject the hypothesis of CRS at the 5% significance level.**

<sup>14</sup> A possible alternative explanation is that the negative sign of own-industry ICT investment is due to a product market rivalry (or business stealing) effect, whereby companies that find new and more efficient applications by ICT usage will negatively affect the productivity of their competitors (Bloom et al. 2013). Product market rivalry is likely to be more common among competitors than among companies operating in different industries.

<sup>15</sup> We constructed an intra-industry and an inter-industry measure of R&D capital per worker. The latter used the same weighting scheme adopted to build the inter-industry ICT variable. However we find that this variable created problems due to collinearity issues. For example, while the correlation

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between inter-industry ICT and inter-industry R&D for the whole sample is around 0.6, in some industries it goes up to 0.9. Hence collinearity is an issue when trying to control for too many industry factors, particularly when the inter-industry spillover variables use the same weights. Therefore all robustness checks use intra-industry R&D.

<sup>16</sup> See also Hall (1988) and Vecchi (2000).

<sup>17</sup> Similar results are obtained using real industry output as a control variable. This check aimed to verify whether possible measurement errors associated with the use of industry deflators (in place of firm-specific prices) were driving our results (Klette and Griliches 1996).

<sup>18</sup> Equation (6) is estimated with the Newey-West estimator in order to control for serial correlation and arbitrary heteroskedasticity.

<sup>19</sup> We also computed the total spillover effect using the coefficients in column (3). Similar to the results in Table 5 we found that only companies at the higher end of the R&D distribution can offset the negative ICT intra industry spillover.

<sup>20</sup> **More specifically, the F statistics refers to the weak instrument test by Stock and Yogo (2005). The rule of thumb is that an F statistics above 16 indicates that the instruments are valid.**

<sup>21</sup> We also considered a specification which includes inter-industry R&D instead of intra-industry. In this case the results are closer to those presented in columns (1) - (3), with a positive inter-industry ICT spillover at time  $t-5$ . Therefore, parameters reported on the right-hand side of the table have to be considered as lower bound values.

<sup>22</sup> **We are particularly grateful to one reviewer for raising this point.**

<sup>23</sup> **In the five-year lag specification the capital per worker variable is no longer statistically significant. This suggests that there might be some miss-specification when considering longer lags. To investigate this issue we run the specification without imposing constant returns to scale (i.e. without expressing variables in per worker terms). In this case the capital coefficient is statistically significant and results for the other coefficients are consistent with those presented in Table 6. Results are available upon request.**

<sup>24</sup> The literature has generally found complementarity between ICT and skilled labour (Bresnahan, Brynjolfsson and Hitt 2002), while the complementarity between R&D and ICT is more dubious (Hall et al. 2013). This means that we cannot rule out the fact that the declining role of absorptive capacity is a consequence of the proxy we use. Expanding on this issue is beyond the scope of this paper but further analysis on the changes of absorptive capacity over time warrant future research effort.

<sup>25</sup> We also tried to assess the lagged impact of ICT using a dynamic specification, i.e. including the lagged dependent variable on the right hand side of the equation. The main results on the ICT spillover effect were confirmed. However, coefficient estimates of the company-level variables were unstable; therefore we decided to use a static specification.

<sup>26</sup> These results also rule out the presence of business stealing effect as one of the two alternative explanations of the negative intra-industry spillover effect discussed in Section 5.1, footnote 14. In fact, it would be difficult to argue that market rivalry decreases over time.